TOWARD AN OPERATIONAL METHOD FOR REFINED SNOW CHARACTERIZATION USING DUAL-POLARIZATION C-BAND SAR DATA

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ABSTRACT

This paper presents a method to characterize snow cover at a massif scale using dual-polarization C-band SAR data. It is demonstrated that it is crucial to exactly model the distribution of liquid water inside the snowpack in order to perform accurate snow characterization at C-band. Consequently, the key point of this new method consists in using a multi-layer meteorological snow model. Based on a validated multi-layer electromagnetic backscattering model, SAR data and snow profiles estimated by the weather model can be combined. Adequate spatial reorganization of these snow profiles leads to a refined snow characterization. Accurate snow monitoring like Liquid Water Content is presented, opening the way for a new operational method.

Index Terms— Synthetic Aperture Radar, Snow, Remote Sensing

1. INTRODUCTION

Many studies using airborne or spaceborne Microwave SAR have been carried out in order to estimate both qualitatively and quantitatively the snow cover. By example at C-band, wet snow mapping can be performed successfully using threshold method [1]. Concerning snow inversion, methods are mainly based on a single-layer assumption and a one/two dimensional minimization approach. Nevertheless, snow cover is made up of various layers having different properties. Furthermore, at C-band, the approximate permittivities of water and dry snow are of the order \((66 + j36)\varepsilon_0\) and \((1.5 + j10^{-4})\varepsilon_0\) respectively. A small proportion of liquid water in the snow will lead to particular properties for wave diffusion and attenuation.

In spite of the aforementioned discrepancy, a new method for refined snow characterization is presented in this paper. The key point consists in combining a multi-layer snow electromagnetic backscattering model, dual-polarization SAR data and a snow meteorological model. Consequently, Section 2 presents this weather snow model called CROCUS. Then, Section 3 describes the properties and the capabilities of the EM model. Finally, the next Section introduces the new methodology whereas Section 5 shows some results.

For this study, CROCUS simulations and ASAR / ENVISAT data are available for the French Alpes “Grandes Rousses” massif from February to July 2004.

2. CROCUS SNOW ACCUMULATION MODEL

To monitor the spatial variability of the snow cover at a massif scale, snow profiles can be estimated by means of the meteorological model SAFRAN / CROCUS developed by “Météo France” [2].

Initially, SAFRAN estimates relevant meteorological parameters affecting snow pack evolution. The observed weather data (precipitation, solar radiation, air humidity, wind, air temperature) are provided continuously by various networks (automatic observations, French Snow/Weather network, in situ measurements...). A spatialisation of these data are realized over each massif by 300 m steps and for six orientations (North, West, South West, South, South East, East). Afterwards, CROCUS, which is a snow numerical model, calculates the energy and mass evolution of snowpack from SAFRAN outputs. It simulates the physical processes inside the snowpack and its stratigraphy (up to 50 different layers). Slope elevation effect is taken into account by 20 degree steps. Snow density \(\rho^k\), snow moisture \(\upsilon_{lw}^k\), and snow thickness \(dz^k\) are estimated for each layer \(k\). Consequently, Liquid Water Content or Snow Water Equivalent can be accurately calculated taking into account the different layers. Concerning snow grains, new formalisms were introduced in

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order to describe all natural snow types: the dendricity and the sphericity. For freshly fallen snow layer (called dendritic snow), the dendricity describes the proportion of original crystal shapes which are still remaining. Sphericity indicates the ratio of rounded versus angular shapes. For rounded snow layer (called non-dendritic when dendricity reaches 0), CROCUS gives also the sphericity and the optical diameter.

This chain has been validated many times since 1992 and is operationally used by French avalanche forecasters [3]. However, depending on the ground under the snowpack, vegetation, or local topography, wind effect may modify the spatial variability of the snow cover. Finally, its segmentation at a massif scale seems to be limited as compared to SAR resolution.

3. MULTILAYER EM BACKSCATTERING MODEL

In order to perform a refined snow monitoring, a snow EM backscattering model is introduced. To avoid the loss of the comprehensive information given by CROCUS, this study is focused on a multilayer approach.

3.1. Main features

Based on the Vectorial Radiative Transfer equation, the EM backscattering model is adapted to multi-layer snowpack. By using the first-order Mueller matrix solution of the VRT, the integration domain with respect to snow cover thickness can be identified [4]. Considering that internal refraction is neglected inside layered snow pack, the integration domain is divided into discrete layers. It is then possible to add up the different contributions of each layer. Accordingly, each layer \( k \) may have its own properties such as moisture or particle size depending on metamorphosis effects. In this model, each layer is considered as a collection of spherical ice particles with radius \( r_{\text{ice}}^k \), surrounded by a thin water film of radius \( r_{\text{sca}}^k \), which tends to \( r_{\text{ice}}^k \) in the case of dry scatters. The permittivity of these scatters, \( \varepsilon_{\text{sca}}^k \), is calculated by using a multi-layer assumption [5]. This approach leads to a two-phase model: dry/wet spherical ice particles embedded in air.

Moreover, the Strong Fluctuation Theory is used [6] in order to take into account coherent effects in the medium. Even if snow EM backscattering depends on the size and shape of water inclusions, the correlation lengths of water inclusions in vertical and horizontal direction have to be determined with high accuracy. Furthermore, these parameters are experimentally very difficult to obtain and are not given by CROCUS. In this way, phase matrix \( P \) and extinction coefficient \( \kappa_e \) are derived by using SFT and spherical symmetric correlation function. The correlation length is derived from Stogryn’s model [7] and adapted to this two-layer spherical assumptions. To link the dendricity/sphericity CROCUS formalism to this sphericity assumption, formulas inspired by [8] are worked out.

The cross-polarization channel can not be accurately calculated from this method. Thus, this EM model has been validated at local scale for VV channel using both in situ snow measurements and CROCUS snow profiles [9].

3.2. First EM Simulation at a Massif Scale

To simulate VV backscattering at massif scale, input parameters (soil and snow parameters, local incidence angle) must be defined. First, soil parameters such as moisture (i.e permittivity) or rms surface height are estimated with summer snow free image by using Oh inversion adapted to dual-polarization case [10]. Some refinements are defined in [11] in order to retrieve a wider range of roughness. Given the rms height \( s \) and the volumetric soil moisture content \( m_e \), an optimization on the correlation length of the soil roughness \( l_s \) is performed by minimizing the quadratic error between IEM simulation and data. Local incidence angles are derived by geo-referencing a 50 meter Digital Elevation Model in the slant range projection. Snow EM backscattering can be simulated using the estimated soil parameters, local incidence angles and \( p_{\text{init}} \) snow profiles initially calculated by CROCUS over a part of massif. The results are shown in Fig.1. Grey color indicates areas where the local incidence angle is above 55°.

It appears that CROCUS snow profiles \( p_{\text{init}} \) can be used to take a holistic approach to snow cover EM backscattering. However, EM simulation with CROCUS profiles can deviate in a larger way from SAR data. Indeed, with the limited resolution of CROCUS as compared to the SAR one, the spatial variability of snow cover need to be further improved.
4. NEW METHODOLOGY

To solve this problem and retrieve accurate snow parameters, a new method based on the multi-layer EM model, dual polarization SAR data and CROCUS snow profiles is proposed.

First, a part of the initial profiles calculated by CROCUS may be considered as correct. Given the powerful application already used with CROCUS [3] but its limited segmentation, selection of 33% of the overall pixels may be a good compromise. This rate corresponds to a threshold between VV simulation and data below 1.5dB. For each one of these pixels, its CROCUS snow profile is considered as optimal \( p_{opt} \). Consequently, for each erroneous pixel, it is necessary to find an appropriate snow profile using the following two steps.

4.1. Selection of possible snow profiles set

The adopted approach is based on the spatial reorganization of the snow cover proposed by CROCUS. Why will it not be possible for a erroneous pixel to have the snow profile of one of its neighborhood? On the first hand, its neighborhood must be limited. In fact, in order to avoid exhaustive time calculation and unrealistic solution, the number of initial snow profiles given by CROCUS must be reduced. Indeed, CROCUS calculates more than 150 different profiles for a unique massif. However, it appears unlikely that a profile originally simulated for an altitude of 3000 meters by CROCUS can be assigned to a pixel at 1950 meters. That is why some decision rules are taken in order to eliminate the furthest CROCUS profiles. A list of probable profiles \( \mathcal{P}_{pix-list} \) can be constructed for each erroneous pixel denoted \( pix \).

4.2. Minimization using specific weighting

For each \( p \) snow profile among the list \( \mathcal{P}_{pix-list} \), VV backscattering \( \sigma_{0,vv,\theta} \) can be simulated using our multilayer EM model. For each erroneous pixel, the error minimization between simulations and \( \sigma_{0,vv,\theta} \cdot \sigma_{0,vv,\theta} \) datums leads to a new snow cover profile retrieval. Even if cross-polarization channel can not be simulated as seen in Section 3, this information can be used as a weighting in this minimization process. Consequently, the following steps are carried out:

1) All previously validated pixels having \( p \) snow profile and having the same incidence angle as the considered pixel \( (\theta_{pix} \pm 10\degree) \) are defined by \( E_p(\theta_{pix}) \) set. The relative standard deviation \( Q_{p,v} \cdot \sigma_{0,vh,\theta} \) among all \( \sigma_{0,vh} \) may be a good indicator for the weighting.

\[
\omega_p \propto Q_{p,v} = \left( \frac{\text{mean}_{E_p(\theta_{pix})} \left( \sigma_{0,vh} - \sigma_{0,vh,\theta} \right)^2}{\sigma_{0,vh,\theta}^2} \right) \]

2) The weight \( \omega_p \) associated to \( p \) snow profile can be described by an affine function depending on \( Q_{p,v} \) and \( Q_{p,v} \) for dual polarization SAR data. In case of full POLSAR data, relevant polarimetric parameters such as the H-A-\( \alpha \) may be added in this weighting process.

3) Finally, the optimum snow profile \( p_{opt} \) satisfies the following relation:

\[
p_{opt} = \arg \min_{p \in \mathcal{P}_{pix-list}} \left( \omega_p \cdot \left( \sigma_{0,vv,\theta}^0(p) - \sigma_{0,vv,\theta}^0 \right) \right) \]

4.3. 1-D minimization for non-improvable profile

In the case for which no other CROCUS profile leads to a better estimation of EM backscattering, the most inaccurate snow variable is determined. By keeping the initial profile calculated by CROCUS and modifying the erroneous variable, the error between simulation and datum can be minimized. However, the aim of this paper is not to provide an accurate classical minimization based on snow parameters modifications. Even if the performance of this method could be much better, this step is only used when \( p_{opt} \) is identical to \( p_{init} \) after (2).

4.4. Results and discussion

Finally, EM backscattering can be simulated using \( p_{opt} \) snow profiles as shown in Fig. 1. Furthermore, the overall performances of this method are summarized in the following Table.

<table>
<thead>
<tr>
<th>Date</th>
<th>Bias (dB)</th>
<th>RMSE (dB)</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>16th Feb.</td>
<td>-0.117 / +0.022</td>
<td>3.034 / 1.441</td>
<td>0.249 / 0.624</td>
</tr>
<tr>
<td>22nd Mar.</td>
<td>-0.305 / -0.042</td>
<td>3.146 / 1.954</td>
<td>0.173 / 0.719</td>
</tr>
<tr>
<td>8th Apr.</td>
<td>+1.410 / -0.033</td>
<td>3.935 / 1.458</td>
<td>0.194 / 0.695</td>
</tr>
<tr>
<td>26th Apr.</td>
<td>+0.599 / +0.512</td>
<td>2.632 / 1.803</td>
<td>0.105 / 0.345</td>
</tr>
<tr>
<td>13th May</td>
<td>+1.801 / +0.976</td>
<td>3.722 / 2.241</td>
<td>0.045 / 0.285</td>
</tr>
<tr>
<td>31st May</td>
<td>-0.676 / -0.277</td>
<td>3.762 / 2.408</td>
<td>0.109 / 0.590</td>
</tr>
</tbody>
</table>

For all of these indicators, it clearly appears that some refinements have been realized. However, some trends can be observed depending on the acquisition date. Bias and \( R^2 \) can be perfectly corrected for the first three dates, as opposed to the 26th of April and the 13th of May. Three main reasons may explain these limited results.

1) Following Step 4.2, some snow profiles have been optimized with inadequate profiles. In regards to in-situ snow measurements, the optimization process may not be perfectly performed due to erroneous initial CROCUS calculation.

2) The number of initial CROCUS profiles tend to decrease in an overall manner due to melting process. For pixels nearby the snow line, the number of available snow profiles is lower and the algorithm’s performance may be limited.
3) At the end of the snow melting period, some natural media under the snow may appear. Given the fact that the soil properties are calculated using summer SAR data, some characteristics such as the soil moisture may have changed.

In spite of these drawbacks, the presented method shows good results. Furthermore, due to the fact that new snow profiles come from CROCUS model, they are totally realistic.

5. APPLICATION AND CONCLUSION

Consequently, accurate snow monitoring like Snow Water Equivalent, Liquid Water Content and snow height mapping can be realized. As a possible application, Liquid Water Content mapping is shown in Fig. 2 and compared to wet snow mapping using SAR based method. Nägler’s method [1] is taken as a reference using a sigmoid activation function \( F_a \) centered at \(-3dB\) instead of a simple threshold in order to take into account different uncertainties such as the effect of the vegetation [12]. The output range of \( F_a \) between 0 and 1 can be seen as an estimator of wet snow probability.

It can be clearly observed that a good compromise seems to be found between SAR based method and initial CROCUS simulation. Using threshold method, how would it be possible to detect all kind of snowpack undergoing melting process? Then, the limited resolution of CROCUS seems to be solved too. CROCUS segmentation is clearly refined and accurate snow monitoring in a spatial point of view can be now performed.

6. REFERENCES


